MODELING THE AUTOREGRESSIVE CAPITAL ASSET PRICING MODEL FOR TOP 10 SELECTED SECURITIES IN BSE

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ABSTRACT

Systematic risk is the uncertainty inherent to the entire market or entire market segment and Unsystematic risk is the type of uncertainty that comes with the company or industry we invest. It can be reduced through diversification. The study generalized for selecting of nonlinear capital asset pricing model for top securities in BSE and made an attempt to identify the marketable and non-marketable risk of investors of top companies. The analysis was conducted at different stages. They are Vector auto regression of systematic and unsystematic risk.

Key words: Systematic Risk, Unsystematic Risk and Vector Auto Regression

http://www.iaeme.com/ijm/index.asp

INTRODUCTION AND RELATED WORK

The capital asset pricing model (CAPM) of William Sharpe (1964) and John Lintner (1965) marks the birth of asset pricing theory (resulting in a Nobel Prize for Sharpe in 1990). Four decades later, the CAPM is still widely used in applications, such as estimating the cost of capital for firms and evaluating the performance of managed portfolios. The CAPM builds on the model of portfolio choice developed by Harry Markowitz (1959). In Markowitz’s model, an investor selects a portfolio at time t=1 that produces a stochastic return at t. The model assumes investors are risk averse and, when choosing among portfolios, they care only about the mean and variance of their one-period investment return. As a result, investors choose “mean variance- efficient” portfolios, in the sense that the portfolio The capital asset pricing model (CAPM) is used to determine a theoretically appropriate required rate of return of an asset, if that asset is to be added to an already well-diversified portfolio, given that asset’s non-diversifiable risk. The model takes into account the asset's sensitivity to non-diversifiable risk (also known as systematic risk or market risk, often represented by the quantity beta.
The capital asset pricing model (CAPM) is the standard risk-return model used by most academicians and practitioners. The underlying concept of CAPM is that investors are rewarded for only that portion of risk which is not diversifiable. This non-diversifiable risk is termed as beta, to which expected returns are linked.

It is mandatory to review the literature available with respect to the area of research study. Several studies have been undertaken to analyze the capital asset price model. The present chapter presents some of the studies conducted by the analysts in the past. Michael C. Jensen (1972) provides considerable attention has recently been given to general equilibrium models of the pricing of capital assets. Of these, perhaps the best known is the mean-variance formulation originally developed by Sharpe (1964) and Treynor (1961), and extended and clarified by Lintner (1965a; 1965b), Mossin (1966), Fama (1968a; 1968b), and Long (1972). In addition, Treynor (1965), Sharpe (1966), and Jensen (1968; 1969) have developed portfolio evaluation models which are either based on this asset pricing model or bear a close relation to it. In the development of the asset pricing model it is assumed that (1) all investors are single period risk-averse utility of terminal wealth maximizers and can choose among portfolios solely on the basis of mean and variance, (2) there are no taxes or transactions costs, (3) all investors have homogeneous views regarding the parameters of the joint probability distribution of all security returns, and (4) all investors can borrow and lend at a given riskless rate of interest. The main result of the model is a statement of the relation between the expected return on an asset and its beta factor from the mean-variance formulation. The evidence presented in Section II indicates the expected excess return on an asset is not strictly proportional to its beta, and we believe that this evidence, coupled with that given in Section IV, is sufficiently strong to warrant rejection of the traditional form of the model given by (1). We then show in Section III how the cross-sectional tests are subject to measurement error bias, provide a solution to this problem through grouping procedures, and show how cross-sectional methods are relevant to testing the expanded two-factor form of the model. We show in Section IV that the mean of the beta factor has had a positive trend over the period 1931–65 and was on the order of 1.0 to 1.3% per month in the two sample intervals we examined in the period 1948–65.

This seems to have been significantly different from the average risk-free rate and indeed is roughly the same size as the average market return of 1.3 and 1.2% per month over the two sample intervals in this period. This evidence seems to be sufficiently strong enough to warrant rejection of the traditional form of the model given by (1). In addition, the standard deviation of the beta factor over these two sample intervals was 2.0 and 2.2% per month, as compared with the standard deviation of the market factor of 3.6 and 3.8% per month. Thus the beta factor seems to be an important determinant of security returns. Tim Bollerslev et al. (1988) examines the capital asset pricing model provides a theoretical framework for the pricing of assets with uncertain returns. The premium to induce risk-averse investors to bear risk is proportional to the covariance of the asset return with the market portfolio return. In this paper a multivariate generalized autoregressive conditional heteroscedastic process is estimated for returns to bills, bonds, and stock. It is observed that the expected return is proportional to the conditional covariance of each return with that of a fully diversified or market portfolio. It is found that the conditional covariance’s are quite variable over time and are a significant determinant of time-varying risk premia. Also time-varying and forecastable. However, there is evidence that other variables including innovations in consumption should also be considered in the investor's information set when estimating the conditional distribution of returns. Viral V. Acharya et al. (2005) examines explicitly a simple equilibrium model with liquidity risk. In our liquidity-adjusted capital asset pricing model, a security’s required return depends on its expected liquidity as well as on the covariance’s of its own return and liquidity with the market return and liquidity. In addition, a persistent negative shock to a security’s liquidity results in low contemporaneous returns and high predicted future returns. The model provides a unified framework for understanding the various channels through which liquidity risk may affect asset prices. Our empirical results shed light on the total and relative economic significance of these channels and provide evidence of flight to liquidity. Peter Hordahl et al. (2007)
This paper reviews analytical work carried out by central banks that participated at the Autumn Meeting of Central Bank Economists on “Understanding asset prices: determinants and policy implications”, which the BIS hosted on 30–31 October 2006. The paper first discusses some general properties of asset prices, focusing on volatilities and co-movements. It then reviews studies that look at determinants of asset prices and that attempt to estimate a fair value of assets. The next part of the paper focuses on research that aims at measuring the impact of changes in asset wealth on the real economy. It then goes on to discuss how central banks use information from asset prices to develop indicators of market expectations that are useful for monetary policy purposes. Finally, the paper reviews central banks’ views on whether monetary policy should react in a direct way to asset price developments. Javed iqbalet al(2007) This study investigates the applicability of the CAPM in explaining the cross section of stock return on the Karachi Stock Exchange for the period September 1992 to April 2006. Unlike earlier studies on emerging markets this study is carried out with a broader scope. Firstly, the tests are conducted on individual stocks as well as size sorted portfolios and industry portfolios. Secondly, the test accounts for the intervalling affect by employing three data frequencies namely daily, weekly and monthly data. Thirdly, keeping in view the infrequent trading prevailing in emerging markets in general and Pakistan’s equity markets in particular the test is also carried out on beta corrected for thin trading, using the Dimson (1979) procedure. Contrary to earlier studies on emerging markets the premium for beta risk and the skewness have the expected signs. The risk return relationship however appears to be non-linear and is most profound in recent years when the market performance, backed by the high level of liquidity and trading activity, was outstanding. David e. allen et al (2009) empirically examines the behavior of the three risk factors from Fama-French Three Factor model of stock returns, beyond the mean of the distribution, by using quantile regressions and a US data set. The study not only shows that the factor models does not necessarily follow a linear relationship but also shows that the traditional method of OLS becomes less effective when it comes to analyzing the extremes within a distribution, which is often of key interest to investors and risk managers. John hunter et al (2009) provides a multifactor model of UK stock returns is developed, replacing the conventional consumption habit reference by a relation that depends on US wealth two step Instrumental Variables and Generalized Method of Moments estimators are applied to reduce the impact of weak instruments.

The standard errors are corrected for the generated regressor problem and the model is found to explain UK excess returns by UK consumption growth and expected US excess returns. Hence, controlling for nominal effects by subtracting a risk free rate and conditioning on real US excess returns provides a coherent explanation of the equity premium puzzle. Mohammad hasmat ali et al (2010) aims to test the validity of the capital asset pricing model in the Dhaka Stock Exchange of Bangladesh. The study period for the study covers from July 1998 to June 2008. The sample of the study is 160 companies listed at Dhaka Stock Exchange. We attempt to investigate the relation between risk (beta) and return by using the Fama and Macbeth (1973) approach. We find that there is a relation between risk and return but the relation is not linear and beta cannot be considered as the main and only source of risk. This study concludes on weak practical implication of CAPM in emerging stock markets. It is recommended to consider other important variables to find an effective pricing mechanism. It is also recommended to apply some other methodologies to validate the CAPM. Amit goyal (2011) review the state of empirical asset pricing devoted\ to understanding cross sectional differences in average rates of return.

Both methodologies and empirical evidence are surveyed. Tremendous progress has been made in understanding return patterns. At the same time, there is a need to synthesize the huge amount of collected evidence. S. Saravanan et al (2013) examines the CAPM is used to determine a theoretically appropriate, required rate of return for an asset, if that asset is to be added to an already well-diversified portfolio, given that assets have non-diversifiable risk. The model takes into account the asset’s sensitivity to systematic risk, often represented by the quantity, beta, and the expected return of a theoretical risk-free asset. The CAPM says that expected return of a security or a portfolio equals the rate on a risk-free security plus a risk premium. If this expected return does not meet or beat the required return, then the investment should not be undertaken. The security market line plots the result of CAPM for all different risks (betas). Josipa dzaja et al (2013) examines if the Capital Asset Pricing Model (CAPM) is adequate for capital asset valuation on the central and South-East European emerging securities markets using monthly stock returns for nine countries for the period of January 2006 to December 2010. Precisely, it is tested if beta, as the systematic risk measure, is valid on
observed markets by analyzing are high expected returns associated with high levels of risk, i.e. beta. Also, the efficiency of market indices of observed countries is examined. Hamidreza vakili Fard and Amin Babei Falah (2015) introduced a new CAPM to forecast the expected rate of return in a more befitting manner. They first provide a brief for a development of the CAPM and its pros and cons. Then they try and establish their new CAPM model. The main difference of their model is the use of two betas. In the end. In the end they use the listed basic metals companies to present a practical example of the application of the proposed model. Stefan Daniel and Josef glova (2015) explores CAPM in its dynamic time-varying form generally applicable in determination of equity costs within business valuation process. They briefly describe the literature on the CAPM and general index model specifying risk premium and equity costs determination.

Their short discussion of the published literature suggests that while the CAPM is still popular with the professional practice, its effectiveness for risk premium determination is limited. So in the next part we shortly describe the applicability of the time-varying CAPM as an augmented approach to the traditional CAPM form. To illustrate applicability of the model they employ this augmented concept by incorporating only unexpected changes in the autoregressive time series models in a specified company Dell Inc. In the final part they discuss achieved results and their possible applicability in equity risk premium determination. Distribution fitting and simulation techniques have been also used to provide more viable results of equity costs.

**METHODOLOGY AND TECHNIQUES OF DATA ANALYSIS**

For the purpose to evaluate the systematic risk and unsystematic risk of investors the authors selected top 10 companies listed in BSE 30. The top 10 companies are Reliance industries, Bharat Heavy Electricals limited (BHEL), Hindustan Unilever (HUL), ITC, National Thermal Power Corporation Limited (NTPC), State Bank of India (SBI), Maruthi Suzuki, Larsen & Toubro (L & T), Tata Consultancy services (TCS) and Tata motors. The analysis was conducted at different stages. Stage 1 Univariate Normality test of the top companies in BSE. Stage 2 Selection of maximum lag length with security return for each company. Stage 3 Vector auto regression in CAPM of top companies in BSE. Vector autoregression (VAR) is an econometric model used to capture the linear interdependencies among multiple time series. VAR models generalize the univariate autoregression (AR) models by allowing for more than one evolving variable. All variables in a VAR are treated symmetrically in a structural sense each variable has an equation explaining its evolution based on its own lags of the other model variables. VAR modeling does not require as much knowledge about the forces influencing a variable as do structural models with simultaneous equations: The only prior knowledge required is a list of variables which can be hypothesized to affect each other intertemporally.

**DEFINITION**

A VAR model describes the evolution of a set of k variables (called endogenous variables) over the same sample period (t = 1, ..., T) as a linear function of only their past values. The variables are collected in a k × 1 vector y_t, which has as the j-th element, y_{it}, the time t observation of the i-th variable. For example, if the i-th variable is GDP, then y_{it} is the value of GDP at time t.

A p-th order VAR, denoted VAR (p), is

\[
y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + e_t,
\]

where the l-periods back observation y_{t-l} is called the l-th lag of y, c is a k × 1 vector of constants (intercepts), A_i is a time-invariant k × k matrix and e_t is a k × 1 vector of error terms satisfying

\[
E(e_t) = 0 \quad \text{every error term has mean zero;}
\]

\[
E(e_t e'_t) = \Omega \quad \text{the contemporaneous covariance matrix of error terms is } \Omega \text{ (a k × k positive-semidefinite matrix);}
\]

\[
E(e_t e'_{t-k}) = 0 \quad \text{for any non-zero } k \quad \text{there is no correlation across time; in particular, no serial correlation in individual error terms. See Hatemi-J (2004) for multivariate tests for autocorrelation in the VAR models.}
\]

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A pth-order VAR is also called a **VAR with p lags**. The process of choosing the maximum lag p in the VAR model requires special attention because inference is dependent on correctness of the selected lag order.

**ORDER OF INTEGRATION OF THE VARIABLES**

Note that all variables have to be of the same order of integration. The following cases are distinct:

- All the variables are I(0) (stationary): one is in the standard case, i.e., a VAR in level.
- All the variables are I(d) (non-stationary) with d > 0.
- The variables are cointegrated: the error correction term has to be included in the VAR. The model becomes a Vector error correction model (VECM) which can be seen as a restricted VAR. The variables are not cointegrated: the variables have first to be differenced d times and one has a VAR in difference.

**CONCISE MATRIX NOTATION**

One can stack the vectors in order to write a VAR (p) with a concise matrix notation:

\[ Y = BZ + U \]

Details of the matrices are in a separate page.

**Example**

For a general example of a VAR (p) with k variables, see General matrix notation of a VAR (p).

A VAR (1) in two variables can be written in matrix form (more compact notation) as

\[
\begin{bmatrix}
y_{1,t} \\
y_{2,t}
\end{bmatrix} =
\begin{bmatrix}
c_1 \\
c_2
\end{bmatrix} +
\begin{bmatrix}
A_{1,1} & A_{1,2} \\
A_{2,1} & A_{2,2}
\end{bmatrix}
\begin{bmatrix}
y_{1,t-1} \\
y_{2,t-1}
\end{bmatrix} +
\begin{bmatrix}
e_{1,t} \\
e_{2,t}
\end{bmatrix},
\]

where only a single A matrix appears because this example has a maximum lag p equal to 1.

or, equivalently, as the following system of two equations:

\[
y_{1,t} = c_1 + A_{1,1}y_{1,t-1} + A_{1,2}y_{2,t-1} + e_{1,t}
\]

\[
y_{2,t} = c_2 + A_{2,1}y_{1,t-1} + A_{2,2}y_{2,t-1} + e_{2,t}.
\]

Each variable in the model has one equation. The current (time t) observation of each variable depends on its own lagged values as well as on the lagged values of each other variable in the VAR.

**WRITING VAR (P) AS VAR (1)**

A VAR with p lags can always be equivalently rewritten as a VAR with only one lag by appropriately redefining the dependent variable. The transformation amounts to stacking the lags of the VAR (p) variable in the new VAR (1) dependent variable and appending identities to complete the number of equations.

For example, the VAR (2) model

\[
y_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = c + A_{1} y_{t-1} + A_{2} y_{t-2} + \epsilon_t
\]

Can be recast as the VAR (1) model

\[
\begin{bmatrix}
y_t \\
y_{t-1}
\end{bmatrix} =
\begin{bmatrix}
c \\
0
\end{bmatrix} +
\begin{bmatrix}
A_1 & A_2 \\
I & 0
\end{bmatrix}
\begin{bmatrix}
y_{t-1} \\
y_{t-2}
\end{bmatrix} +
\begin{bmatrix}
e_t \\
0
\end{bmatrix},
\]

where I is the identity matrix.
The equivalent VAR (1) form is more convenient for analytical derivations and allows more compact statements.

**STRUCTURAL VAR**

A structural VAR with p lags (sometimes abbreviated SVAR) is

\[
B_0y_t = c_0 + B_1y_{t-1} + B_2y_{t-2} + \cdots + B_py_{t-p} + \epsilon_t,
\]

where \( c_0 \) is a \( k \times 1 \) vector of constants, \( B_i \) is a \( k \times k \) matrix (for every \( i = 0, \ldots, p \)) and \( \epsilon_t \) is a \( k \times 1 \) vector of error terms. The main diagonal terms of the \( B_0 \) matrix (the coefficients on the \( i \)th variable in the \( i \)th equation) are scaled to 1.

The error terms \( \epsilon_t \) (structural shocks) satisfy the conditions (1) - (3) in the definition above, with the particularity that all the elements off the main diagonal of the covariance matrix \( \mathbb{E}(\epsilon_t \epsilon_t') = \sum \) are zero. That is, the structural shocks are uncorrelated.

For example, a two variable structural VAR(1) is:

\[
\begin{bmatrix}
1 & B_{0;1,2} \\
B_{0;2,1} & 1
\end{bmatrix}
\begin{bmatrix}
y_{1,t} \\
y_{2,t}
\end{bmatrix}
= 
\begin{bmatrix}
c_{0;1} \\
c_{0;2}
\end{bmatrix}
+ 
\begin{bmatrix}
B_{1;1,1} & B_{1;1,2} \\
B_{1;2,1} & B_{1;2,2}
\end{bmatrix}
\begin{bmatrix}
y_{1,t-1} \\
y_{2,t-1}
\end{bmatrix}
+ 
\begin{bmatrix}
\epsilon_{1,t} \\
\epsilon_{2,t}
\end{bmatrix},
\]

that is, the variances of the structural shocks are denoted (\( i = 1, 2 \)) and the covariance is .

Writing the first equation explicitly and passing \( y_{2,t} \) to the right hand side one obtains

Note that \( y_{2,t} \) can have a contemporaneous effect on \( y_{1,t} \) if \( B_{0;1,2} \) is not zero. This is different from the case when \( B_0 \) is the identity matrix (all off-diagonal elements are zero — the case in the initial definition), when \( y_{2,t} \) can impact directly \( y_{1,t+1} \) and subsequent future values, but not \( y_{1,t} \).

Because of the parameter identification problem, ordinary least squares estimation of the structural VAR would yield inconsistent parameter estimates. This problem can be overcome by rewriting the VAR in reduced form.

From an economic point of view, if the joint dynamics of a set of variables can be represented by a VAR model, then the structural form is a depiction of the underlying, “structural”, economic relationships. Two features of the structural form make it the preferred candidate to represent the underlying relations:

1. Error terms are not correlated. The structural, economic shocks which drive the dynamics of the economic variables are assumed to be independent, which implies zero correlation between error terms as a desired property. This is helpful for separating out the effects of economically unrelated influences in the VAR. For instance, there is no reason why an oil price shock (as an example of a supply shock) should be related to a shift in consumers’ preferences towards a style of clothing (as an example of a demand shock); therefore one would expect these factors to be statistically independent.

2. Variables can have a contemporaneous impact on other variables. This is a desirable feature especially when using low frequency data. For example, an indirect tax rate increase would not affect tax revenues the day the decision is announced, but one could find an effect in that quarter’s data. Properties of the VAR model are usually summarized using structural analysis using Granger causality, Impulse responses and forecast error variance decompositions.

**ESTIMATION OF THE REGRESSION PARAMETER**

\[
Y = BZ + U
\]

The multivariate least squares (MLS) for B yields:

\[
\hat{B} = YZ'(ZZ')^{-1}
\]

It can be written alternatively as:
\[
\text{Vec}(\hat{B}) = (ZZ')^{-1}Z \otimes I_k \text{ Vec}(Y)
\]

Where \( \otimes \) denotes the Kronecker product and Vec the vectorization of the matrix \( Y \).

This estimator is consistent and asymptotically efficient. It is furthermore equal to the conditional maximum likelihood estimator.

As the explanatory variables are the same in each equation, the multivariate least squares estimator is equivalent to the ordinary least squares estimator applied to each equation separately.

**FAMA AND FRENCH THREE FACTOR MODEL**

Fama and French (1993) suggested an alternative to the CAPM that included two additional factors which helped explain the excess returns on a portfolio. In addition to the market factor, or \( R_m - R_f \).

Fama and French added SMB (Small minus Big) and HML (High minus Low). The factor SMB represented the average return on small portfolios (small cap portfolios), less the average return on big portfolios (large cap portfolios). The HML factor represented the average return on value portfolios less the average return on two growth portfolios. The value portfolios represented stocks with a high Book Equtiy (BE)/ Market Equtiy (ME) ratio and the growth portfolios represented the complete opposite with low BE/ME ratios. Fama and French found that the addition of these two factors enabled a more robust explanation of the variability in portfolio returns. The three-factor model is described by equation (3) where the expected excess return on portfolio \( i \) is

\[
E(R_i) = R_f + \beta_f [E(R_m) - R_f] + S_f E(SMB) + h_i E(HML)
\]

And where \( E(R_m) - R_f, E(SMB) \) and \( E(HML) \) are expected premiums, and the factor sensitivities or loadings \( \beta_f, S_f \) and \( h_i \) are the slopes in the time series regression,

\[
R_i - R_f = \alpha_i + \beta_f (R_m - R_f) + S_f SMB + h_i HML + E_i
\]

Fama and French (1992, 1995, 1996, and 2004) share one consistent theme, in that the CAPM with its single beta factor fails to price other risks which contribute to the explanation of a portfolio's expected returns.

**DATA ANALYSIS AND RESULTS**

<table>
<thead>
<tr>
<th>Companies</th>
<th>Doornik-Hansen Test</th>
<th>Shapiro-Wilk W</th>
<th>Lillicefors Test</th>
<th>Jarque-Bera Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>BHEL</td>
<td>17717.8</td>
<td>0.536398</td>
<td>0.140694</td>
<td>3.85664e+006</td>
</tr>
<tr>
<td>HUL</td>
<td>840.856</td>
<td>0.911029</td>
<td>0.0594132</td>
<td>9676.61</td>
</tr>
<tr>
<td>ITC Ltd</td>
<td>8645.1</td>
<td>0.58578</td>
<td>0.0406636</td>
<td>77.3736</td>
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<tr>
<td>TCS Ltd</td>
<td>113.516</td>
<td>0.977391</td>
<td>0.0490394</td>
<td>177.596</td>
</tr>
<tr>
<td>Tata Motors</td>
<td>11513.6</td>
<td>0.5753</td>
<td>0.124392</td>
<td>3.16645e+006</td>
</tr>
<tr>
<td>NTPC Ltd</td>
<td>32.5652</td>
<td>0.989907</td>
<td>0.0390735</td>
<td>40.2681</td>
</tr>
<tr>
<td>Reliance Industries</td>
<td>28.0203</td>
<td>0.991691</td>
<td>0.0327564</td>
<td>32.92</td>
</tr>
<tr>
<td>SBI</td>
<td>58.0503</td>
<td>0.987241</td>
<td>0.124562</td>
<td>2.73905e+006</td>
</tr>
<tr>
<td>L&amp;T</td>
<td>1386.01</td>
<td>0.837178</td>
<td>0.0728607</td>
<td>66834.3</td>
</tr>
<tr>
<td>Maruthi Suzuki</td>
<td>75.0096</td>
<td>983397</td>
<td>0.0518774</td>
<td>110.351</td>
</tr>
<tr>
<td>BSE30</td>
<td>19.1963</td>
<td>0.993427</td>
<td>0.0352214</td>
<td>21.3443</td>
</tr>
</tbody>
</table>

A,b,c,d,p value<0.01

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Table 2 Selection of Lag length

<table>
<thead>
<tr>
<th>Company</th>
<th>Maximized Lag Likelihood</th>
<th>Minimum AIC</th>
<th>Lag Length</th>
</tr>
</thead>
<tbody>
<tr>
<td>BHEL</td>
<td>-25580.4762</td>
<td>5.318894</td>
<td>1</td>
</tr>
<tr>
<td>HUL</td>
<td>-1849.76596</td>
<td>3.847904</td>
<td>1</td>
</tr>
<tr>
<td>ITC Ltd</td>
<td>-2113.88965</td>
<td>4.396448</td>
<td>1</td>
</tr>
<tr>
<td>TCS Ltd</td>
<td>-1913.70026</td>
<td>3.980686</td>
<td>1</td>
</tr>
<tr>
<td>Tata Motors</td>
<td>-2587.10549</td>
<td>5.379243</td>
<td>5</td>
</tr>
<tr>
<td>NTPC Ltd</td>
<td>-1733.72834</td>
<td>3.609612</td>
<td>18</td>
</tr>
<tr>
<td>Reliance Industries</td>
<td>-1733.72834</td>
<td>3.609612</td>
<td>18</td>
</tr>
<tr>
<td>SBI</td>
<td>-2091.36651</td>
<td>4.349671</td>
<td>1</td>
</tr>
<tr>
<td>L&amp;T</td>
<td>-2186.09527</td>
<td>4.546408</td>
<td>1</td>
</tr>
<tr>
<td>Maruthi Suzuki</td>
<td>-1988.28451</td>
<td>4.135586</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 3 Vector auto regression in CAPM of BHEL

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Co-Efficient</th>
<th>Standard Error</th>
<th>T Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.190472</td>
<td>0.102156</td>
<td>-1.865</td>
</tr>
<tr>
<td>(Yt - 1)</td>
<td>-0.0410962</td>
<td>0.0300182</td>
<td>-1.369</td>
</tr>
<tr>
<td>Xt</td>
<td>0.384139</td>
<td>0.0932186</td>
<td>4.121</td>
</tr>
<tr>
<td>Xt – 1</td>
<td>1.02496</td>
<td>0.0940278</td>
<td>10.90</td>
</tr>
</tbody>
</table>

R^2 = 0.123893 p>F 0.001
Systematic Risk                   Unsystematic Risk | Total Value
10359.80          | 10318.29     | 20678.09

Y_t =-0.190472-0.0410962Y_{t-1}+0.384139X_t+1.02496X_{t-1}

Table 4 Vector auto regression in CAPM of HUL

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Co-Efficient</th>
<th>Standard Error</th>
<th>T Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0820225</td>
<td>0.0504411</td>
<td>1.626</td>
</tr>
<tr>
<td>(Yt - 1)</td>
<td>-0.0328453</td>
<td>0.0304565</td>
<td>-1.078</td>
</tr>
<tr>
<td>Xt</td>
<td>0.0573372</td>
<td>0.0459920</td>
<td>1.247</td>
</tr>
<tr>
<td>Xt – 1</td>
<td>0.422642</td>
<td>0.0460471</td>
<td>9.178</td>
</tr>
</tbody>
</table>

R^2 = 0.081025 p>F 0.001
Systematic Risk                   Unsystematic Risk | Total Value
2524.586          | 2514.468     | 5039.054

Y_t =0.082025-0.0328453Y_{t-1}+0.0573372X_t+0.422642X_{t-1}

Table 5 Vector auto regression in CAPM of ITC

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Co-Efficient</th>
<th>Standard Error</th>
<th>T Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0395839</td>
<td>0.0661630</td>
<td>0.5983</td>
</tr>
<tr>
<td>(Yt - 1)</td>
<td>-0.0362301</td>
<td>0.0307894</td>
<td>-1.177</td>
</tr>
<tr>
<td>Xt</td>
<td>0.139151</td>
<td>0.0604327</td>
<td>2.303</td>
</tr>
<tr>
<td>Xt – 1</td>
<td>0.474949</td>
<td>0.0606117</td>
<td>7.836</td>
</tr>
</tbody>
</table>

R^2 = 0.065171 p>F 0.001
Systematic Risk                   Unsystematic Risk | Total Value
4335.429          | 4335.980     | 8689.409

Y_t =0.0395839-0.0362301Y_{t-1}+0.139151X_t+0.474949 X_{t-1}

Dr. G.S. David Sam Jayakumar and W. Samuel, “Modeling The Autoregressive Capital Asset Pricing Model For Top 10 Selected Securities In BSE” – (ICAM 2016)
Table 6 Vector auto regression in CAPM of TCS

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Co-Efficient</th>
<th>Standard Error</th>
<th>T Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.119817</td>
<td>0.0532669</td>
<td>2.249</td>
</tr>
<tr>
<td>(Y_t - 1)</td>
<td>-0.147503</td>
<td>0.0294743</td>
<td>-5.004</td>
</tr>
<tr>
<td>(X_t)</td>
<td>0.228029</td>
<td>0.0485446</td>
<td>4.697</td>
</tr>
<tr>
<td>(X_{t-1})</td>
<td>0.597769</td>
<td>0.0491495</td>
<td>12.16</td>
</tr>
</tbody>
</table>

\[ R^2 = 0.158374 \quad \text{p}<F \quad 0.01 \]

Systematic Risk       | Unsystematic Risk | Total Value |
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>2811.523</td>
<td></td>
<td>5611.777</td>
</tr>
</tbody>
</table>

\[ Y_t = 0.119817 - 0.147503Y_{t-1} + 0.228029X_t + 0.597769X_{t-1} \]

Table 7 Vector auto regression in CAPM of Tata Motors

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Co-Efficient</th>
<th>Standard Error</th>
<th>T Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.00446181</td>
<td>0.103326</td>
<td>0.04318</td>
</tr>
<tr>
<td>(Y_t - 1)</td>
<td>-0.0928764</td>
<td>0.0318568</td>
<td>-2.915</td>
</tr>
<tr>
<td>(X_t)</td>
<td>0.443119</td>
<td>0.0944525</td>
<td>4.691</td>
</tr>
<tr>
<td>(X_{t-1})</td>
<td>1.22838</td>
<td>0.0955808</td>
<td>12.85</td>
</tr>
</tbody>
</table>

\[ R^2 = 0.175099 \quad \text{p}<F \quad 0.001 \]

Systematic Risk       | Unsystematic Risk | Total Value |
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>10559.68</td>
<td></td>
<td>20950.08</td>
</tr>
</tbody>
</table>

\[ Y_t = 0.00446181 - 0.09287464Y_{t-1} + 0.443119X_t + 1.22838X_{t-1} \]

Table 8 Vector auto regression in CAPM of L&T

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Co-Efficient</th>
<th>Standard Error</th>
<th>T Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.0494641</td>
<td>0.0637248</td>
<td>-0.7762</td>
</tr>
<tr>
<td>(Y_t - 1)</td>
<td>-0.0666014</td>
<td>0.0273029</td>
<td>-2.439</td>
</tr>
<tr>
<td>(X_t)</td>
<td>0.165124</td>
<td>0.0582072</td>
<td>2.837</td>
</tr>
<tr>
<td>(X_{t-1})</td>
<td>-1.09155</td>
<td>0.0584666</td>
<td>18.67</td>
</tr>
</tbody>
</table>

\[ R^2 = 0.267515 \quad \text{p}<F \quad 0.001 \]

Systematic Risk       | Unsystematic Risk | Total Value |
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>4040.449</td>
<td>4024.257</td>
<td>8064.706</td>
</tr>
</tbody>
</table>

\[ Y_t = -0.0494641 - 0.0666014Y_{t-1} + 0.165124X_t - 1.09155X_{t-1} \]

Table 9 Vector auto regression in CAPM of Maruthi suzuki

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Co-Efficient</th>
<th>Standard Error</th>
<th>T Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0138608</td>
<td>0.0571264</td>
<td>0.2426</td>
</tr>
<tr>
<td>(Y_t - 1)</td>
<td>-0.0923460</td>
<td>0.0299030</td>
<td>-3.088</td>
</tr>
<tr>
<td>(X_t)</td>
<td>0.233942</td>
<td>0.0522380</td>
<td>4.478</td>
</tr>
<tr>
<td>(X_{t-1})</td>
<td>0.588735</td>
<td>0.0526759</td>
<td>11.18</td>
</tr>
</tbody>
</table>

\[ R^2 = 0.132061 \quad \text{p}<F \quad 0.001 \]

Systematic Risk       | Unsystematic Risk | Total Value |
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>3246.938</td>
<td>3233.923</td>
<td>6480.861</td>
</tr>
</tbody>
</table>

\[ Y_t = 0.0138608 - 0.0923460Y_{t-1} + 0.233942X_t + 0.588735X_{t-1} \]
Table 10 Vector auto regression in CAPM of NTPC

<table>
<thead>
<tr>
<th>Dependent Variable (Y_t)</th>
<th>Co-Efficient (Y_{t-1})</th>
<th>Co-Efficient (X_t)</th>
<th>Co-Efficient (X_{t-1})</th>
<th>Standared Error (Y_{t-1})</th>
<th>Standared Error (X_t)</th>
<th>Standared Error (X_{t-1})</th>
<th>T Ratio (Y_{t-1})</th>
<th>T Ratio (X_t)</th>
<th>T Ratio (X_{t-1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.102094</td>
<td>0.187849</td>
<td>0.566252</td>
<td>0.0434799</td>
<td>0.0324237</td>
<td>0.0394435</td>
<td>2.348</td>
<td>5.794</td>
<td>14.36</td>
</tr>
<tr>
<td>(Y_t - 1)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X_t</td>
<td>0.188936</td>
<td></td>
<td></td>
<td>0.0389880</td>
<td></td>
<td></td>
<td>4.846</td>
<td></td>
<td></td>
</tr>
<tr>
<td>X_{t-1}</td>
<td></td>
<td></td>
<td></td>
<td>0.0394435</td>
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<td></td>
</tr>
<tr>
<td>R^2</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>0.251645</td>
<td></td>
<td>0.001</td>
</tr>
<tr>
<td>p&gt;F</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Systematic Risk: 1713.933
Unsystematic Risk: 1619.479
Total Value: 3333.412

\[ Y_t = 0.102094Y_{t-1} + 0.187849X_t + 0.566252X_{t-1} \]

Table 11 Vector auto regression in CAPM of Reliance Industries

<table>
<thead>
<tr>
<th>Dependent Variable (Y_t)</th>
<th>Co-Efficient (Y_{t-1})</th>
<th>Co-Efficient (X_t)</th>
<th>Co-Efficient (X_{t-1})</th>
<th>Standared Error (Y_{t-1})</th>
<th>Standared Error (X_t)</th>
<th>Standared Error (X_{t-1})</th>
<th>T Ratio (Y_{t-1})</th>
<th>T Ratio (X_t)</th>
<th>T Ratio (X_{t-1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0441659</td>
<td>0.223400</td>
<td>0.939941</td>
<td>0.0455255</td>
<td>0.0324342</td>
<td>0.0421485</td>
<td>0.9701</td>
<td>6.888</td>
<td>22.30</td>
</tr>
<tr>
<td>(Y_t - 1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X_t</td>
<td>0.216965</td>
<td></td>
<td></td>
<td>0.0415716</td>
<td></td>
<td></td>
<td>5.219</td>
<td></td>
<td></td>
</tr>
<tr>
<td>X_{t-1}</td>
<td></td>
<td></td>
<td></td>
<td>0.0421485</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R^2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.397976</td>
<td></td>
<td>0.001</td>
</tr>
<tr>
<td>p&gt;F</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Systematic Risk: 1963.058
Unsystematic Risk: 1854.875
Total Value: 3817.933

\[ Y_t = 0.0441659Y_{t-1} - 0.223400Y_{t-1} + 0.216965X_t + 0.939941X_{t-1} \]

Table 12 Vector auto regression in CAPM of SBI

<table>
<thead>
<tr>
<th>Dependent Variable (Y_t)</th>
<th>Co-Efficient (Y_{t-1})</th>
<th>Co-Efficient (X_t)</th>
<th>Co-Efficient (X_{t-1})</th>
<th>Standared Error (Y_{t-1})</th>
<th>Standared Error (X_t)</th>
<th>Standared Error (X_{t-1})</th>
<th>T Ratio (Y_{t-1})</th>
<th>T Ratio (X_t)</th>
<th>T Ratio (X_{t-1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.0347306</td>
<td>-0.0916188</td>
<td>1.03836</td>
<td>0.0566486</td>
<td>0.0268677</td>
<td>0.0524702</td>
<td>-0.6131</td>
<td>-3.410</td>
<td>19.79</td>
</tr>
<tr>
<td>(Y_t - 1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X_t</td>
<td>0.278347</td>
<td></td>
<td></td>
<td>0.0517242</td>
<td></td>
<td></td>
<td>5.381</td>
<td></td>
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</tr>
<tr>
<td>X_{t-1}</td>
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<td></td>
<td></td>
<td>0.0524702</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>R^2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.303308</td>
<td></td>
<td>0.001</td>
</tr>
<tr>
<td>p&gt;F</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Systematic Risk: 3193.191
Unsystematic Risk: 3180.395
Total Value: 6373.586

\[ Y_t = -0.0347306 - 0.0916188Y_{t-1} + 0.278347X_t + 1.03836X_{t-1} \]

DISCUSSION

Table 1 exhibits the result of the test of normality security return list if top 10 companies in BSE. In order to verify the test of normality in security return we employed four different statistical test(Doornikhanseen Test,Shapiro Wilk W,Lillifors Test,Jarque-Bera Test) respectively the result of the test source the security returns are not normally distributed one percent level of significant. The source return of the company depreciated from normality and the followed non normal distribution. Table 2 visualizes the selection of maximum lag length will security return for each company the maximum the likely loglikelihood returns and the maximum AIC where displayed the result of the analyses source in order to perform for the analysis we have to proceed with maximum lag length of each security returns Table 3 exhibits the result of the extreme Dependent variable fitted as a capital asset pricing model for the company returns of BHEL the result shows the beta value such as (Y_{t-1}), is negative and statistically significant 1% level. This shows if the BSE 30 indices will change then the...
company returns will decrease. Moreover the R² of 0.123893 explain 12.38% variation in the company of BHEL. Finally, the systematic risk of company of BHEL is more and unsystematic risk is less. This shows the market risk of the company of BHEL is less compared to the non-market risk. Table 4 exhibits the result of the extreme Dependent variable fitted as a capital asset pricing model for the company returns of HUL the result shows the beta value such as (Yt,1) is negative and statistically significant 1% level. This shows if the BSE 30 indices will change then the company returns will decrease. Moreover the R² of 0.081025 explain 08.10% variation in the company of HUL. Finally, the systematic risk of company of HUL is more and unsystematic risk is less. This shows the market risk of the company of HUL is less compared to the non-market risk. Table 5 exhibits the result of the extreme Dependent variable fitted as a capital asset pricing model for the company returns of ITC the result shows the beta value such as (Yt,1),Xt,1 is positive and statistically significant 1% level. This shows if the BSE 30 indices will change then the industry returns company will decrease. Moreover the R² of 0.123893 explain 12.38% variation in the company of ITC. Finally, the systematic risk of company of ITC is less compared to the non-market risk. Table 6 exhibits the result of the extreme Dependent variable fitted as a capital asset pricing model for the company returns of BHEL the result shows the beta value such as (Yt,1),1 is negative and statistically significant 1% level.

This shows if the BSE 30 indices will change then the company returns will decrease. Moreover the R² of 0.158374 explain 15.83% variation in the company of ITC. Finally, the systematic risk of company of ITC is more and unsystematic risk is less. This shows the market risk of the company of ITC is less compared to the non-market risk. Table 7 exhibits the result of the extreme Dependent variable fitted as a capital asset pricing model for the company returns of TATA MOTORS the result shows the beta value such as (Yt,1),Xt,1 are positive and statistically significant 1% level. This shows if the BSE 30 indices will change then the company returns will decrease. Moreover the R² of 0.175099 explain 17.50% variation in the company of TATA MOTORS. Finally, the systematic risk of company of TATA MOTORS is more and unsystematic risk is less. This shows the market risk of the company of TATA MOTORS is less compared to the non-market risk. Table 8 exhibits the result of the extreme Dependent variable fitted as a capital asset pricing model for the company returns of L&T the result shows the beta value such as (Yt,1),Xt,1 are negative and statistically significant 1% level. This shows if the BSE 30 indices will change then the company returns will decrease. Moreover the R² of 0.267515 explain 26.75% variation in the company of L&T. Finally, the systematic risk of company of L&T is more and unsystematic risk is less. This shows the market risk of the company of L&T is less compared to the non-market risk. Table 9 exhibits the result of the extreme Dependent variable fitted as a capital asset pricing model for the company returns of MARUTHI SUZUKI the result shows the beta value such as (Yt,1) is negative and statistically significant 1% level.

This shows if the BSE 30 indices will change then the company returns will decrease. Moreover the R² of 0.132061 explain 13.20% variation in the company of MARUTHI SUZUKI. Finally, the systematic risk of company of MARUTHI SUZUKI is more and unsystematic risk is less. This shows the market risk of the company of MARUTHI SUZUKI is less compared to the non-market risk. Table 10 exhibits the result of the extreme Dependent variable fitted as a capital asset pricing model for the company returns of NTPC the result shows the beta value such as (Yt,1),Xt,1 are positive and statistically significant 1% level. This shows if the BSE 30 indices will change then the company returns will decrease. Moreover the R² of 0.251654 explain 25.16% variation in the company of NTPC. Finally, the systematic risk of company of NTPC is more and unsystematic risk is less. This shows the market risk of the company of NTPC is less compared to the non-market risk. Table 11 exhibits the result of the extreme Dependent variable fitted as a capital asset pricing model for the company returns of RELIANCE INDUSTRIES the result shows the beta value such as (Yt,1),Xt,1 are positive and statistically significant 1% level. This shows if the BSE 30 indices will change then the company returns will decrease. Moreover the R² of 0.397976 explain 39.79% variation in the company of Reliance Industries. Finally, the systematic risk of company of Reliance Industries is more and unsystematic risk is less. This shows the market risk of the company of Reliance Industries is less compared to the non-market risk. Table 12 exhibits the result of the extreme Dependent variable fitted as a capital asset pricing model for the company returns of SBI the result shows the beta value such as (Yt,1) is negative and statistically significant 1% level. This shows if the BSE 30 indices will change then the company returns will decrease. Moreover the R² of 0.303308 explain 30.33% variation in the company...
company of SBI. Finally, the systematic risk of company of SBI is more and unsystematic risk is less. This shows the market risk of the company of SBI is less compared to the non-market risk.

After analyzing the top 10 companies data, the following recommendations were suggested to the investors to invest and cautious to invest the market share respectively.

We find that the following company is less risk because the unsystematic risk or marketable risk is less for securities. This shows the market risk of the following companies is less compared to the non-marketable risk of the company. The companies are Reliance industries, BHEL, HUL, ITC, NTPC, SBI, Maruthi Suzuki, L & T, TCS and Tata motors. So investors will made investment in this companies it avoid risk of loss of securities.

CONCLUSION
The result on the study shows that the CAPM in Vector Auto Regression fitted on security returns and company based on information criteria. In fitting the authors selected the best companies Reliance industries, BHEL, HUL, ITC, NTPC, SBI, Maruthi Suzuki, L & T, TCS and Tata motors and calculated the system risk and unsystematic risk of securities of company. So recommend to the investor to invest the non-marketable risk of the companies which are suggested by our findings of study.

REFERENCES